Malaria Modeling and Surveillance

Verification and Validation Report

Part 2

Assessing Malaria Risks in Indonesia
Using Meteorological and Environmental Parameters

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September 7, 2007

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EXECUTIVE SUMMARY

This is the second part of the Verification and Validation (V&V) Report for the Malaria Modeling and Surveillance (MMS) Project. The first part, which concerns malaria in Thailand, was released in July 2006. It was shown that NASA data, models, and output of the MMS project can be used for assessing malaria endemicity and predicting future malaria risk in Thailand. It was also concluded that such information is useful for the decision support needs of the Air Force Special Operations Command (AFSOC) and for its Global Situational Awareness Tool (GSAT). GSAT is a system for assessing environmental and health issues for U.S. overseas forces. In this second part of the report, V&V are performed for malaria in Indonesia.

The goal of the MMS project is to use NASA data, model outputs, and analytical and modeling expertise to enhance the decision support capabilities at AFSOC for malaria risk assessment and control. The technical objectives of the MMS project are: 1) identification of potential larval habitats for major malaria vector species; 2) estimation of current and prediction of future malaria risks; and 3) estimation of spatio-temporal transmission characteristics for cost-effective malaria control.

With a population of 242 million, Indonesia is the fourth most populous and the largest Muslim nation in the world. Situating next to the Strait of Malacca that connects the Indian and the Pacific Oceans, it occupies a significant, strategic location. In recent years, the country has suffered from a series of natural disasters, including the tsunamis in December 2004 in which Indonesia suffered immeasurable loss. The terrorism from extremists and separatists has also drawn world's attention to Indonesia. Indonesia has the third highest malaria endemicity in Southeast Asia after Myanmar and India. Approximately 40% of its population lives in malarious regions.

The distribution of malaria in Indonesia is highly heterogeneous. On Java and Bali, the two islands where about 70% of the population concentrates, malaria is hypoendemic. But on the Outer Islands, which include the rest of the archipelago, malaria ranges from hypo- to hyperendemic. Malaria endemicity had been in decline during the early nineties in Indonesia. But the situation has greatly deteriorated after much of the malaria control efforts were abandoned due to the Asian economy crisis in 1997. Because malaria control efforts are now decentralized to the individual districts, availability of adequate resources and consistency of malaria control practice are of great concerns. The Ministry of Health appears to have limited regulatory authority over the local public health organizations. Lack of reliable data is a serious impedance for more effective reduction of malaria endemicity. The real malaria situation is thought to be much more serious than what is reported.

Currently, approximately half of the cases are falciparum malaria. Mono- and multi-drug resistant falciparum malaria is a concern. The chloroquine resistant vivax malaria in Irian Jaya (Papua) may have a serious consequence on the global efforts of combating malaria if it spreads to other regions. In addition, chloroquine resistant malariae malaria (quartan malaria) has been discovered in Sumatra. Hence Indonesia is the only country in the world where three Plasmodium species have shown drug resistance.

Because there is no centralized clearing house for malaria data in Indonesia, gathering malaria epidemiological data is difficult. We have nevertheless obtained malaria data from: 1) the World Health Organization (WHO) Southeast Asia Regional Office, 2) the Association of South East Asian Nations (ASEAN) Disease Surveillance Network, 3) WHO Roll Back Malaria Menoreh Hills Project, and 4) U.S. Naval Medical Research Unit-2. There are, however, extensive data gaps and inconsistencies within and between datasets. In addition, these data may only reflect the lower bounds of the real malaria endemicty.

Malaria transmission depends on the diverse factors that influence the vectors, parasites, human hosts, and the interactions among them. These factors may include, among others, meteorological and environmental condition, the innate and adapted immunity of the human hosts, public health system, housing standards, vector control, road construction, irrigation projects, population movements, and war-like conditions. The most apparent determinants are the meteorological and environmental factors, such as rainfall, temperature, humidity, and vegetation. When other factors remain more or less constant, the meteorological and environmental conditions can indeed be considered the driving factors.

In an endemic area, the local adult population may acquire sufficient immunity after repeated infections. The disease could be deadly, however, to young children, pregnant women, those with depressed immunoresponse, and people new to the area. Because malaria is virtually nonexistent in the U.S., Americans traveling abroad and U.S. overseas forces are particularly vulnerable. Being the first to arrive in a conflict, and often in areas with minimum public health service, AFSOC personnel faces the greatest threat from malaria.

Although Thailand and Indonesia are both in Southeast Asia and not far apart geographically, they do not have the same climate. The precipitation patterns in Indonesia itself vary significantly from island to island. In addition, Indonesia and Thailand do not share the same malaria vector species. In spite of these differences and the more limited epidemiologic data available in Indonesia, we have shown that the malaria endemicity in Indonesia can be modeled with the same methods as we used on Thailand data.

This shows that malaria risk assessment and predictive techniques developed in the MMS project are not restricted to a specific country. With appropriate remotely sensed meteorological and environmental parameters, epidemiological data and socioeconomic information, the techniques are applicable to other regions of the world.

1. INTRODUCTION

This is the second part of the Verification and Validation (V&V) Report for the Malaria Modeling and Surveillance (MMS) Project. The first part, which concerns malaria in Thailand, was released in 2006.

The technical objectives of the MMS project are: 1) identification of potential larval habitats for major malaria vector species; 2) estimation of current and prediction of future malaria risks; and 3) estimation of spatio-temporal transmission characteristics for cost-effective malaria control. By using the techniques supporting these objectives individually or jointly, a variety of malaria transmission problems can be resolved. The MMS Project will bring the following benefits: 1) reduced morbidity and mortality for local populations and U.S. overseas forces, 2) reduced damage to the environment, and 3) reduced likelihood of larvicide, insecticide and anti-malaria drug resistance.

Thailand is one of the six countries in the Greater Mekong Subregion (GMS). GMS is the world's epicenter of multi-drug resistant falciparum malaria. In Thailand, approximately 50% of the malaria cases are in this category. In the neighboring countries, approximately 90% of the cases are in this categories. Thailand has a long border—nearly 3,200 km over land—with Myanmar, Laos, Cambodia, and Malaysia as its neighboring countries. Attracted by economic opportunities and escaping from military conflicts, significant migrant and transient populations have come into Thailand. Due to the limited accessibility of health care, these populations expand the human reservoir for malaria transmission and escalate the endemicity among the native Thai population. The movement of migrant and transient populations around the border is an important contextual determinant that contributes to malaria transmission. In addition, it confounds the complexity for the prediction of malaria transmission intensity based on meteorological and environmental parameters.

In the first part of the V&V Report, we have shown that NASA data, models, and output of the MMS project can be used for assessing malaria endemicity and predicting future malaria risk in Thailand. We also concluded that such information is useful for the decision support needs of our decision support partner, the Air Force Special Operations Command (AFSOC), and its Global Situational Awareness Tool (GSAT). GSAT is a system for assessing environmental and health issues for U.S. overseas forces.

In this second part of the V&V Report, V&V are performed for malaria in Indonesia. To reduce repetition, only brief descriptions are given for those sections that are common to the first part of the V&V Report. Some useful information, such as a summary of the MMS-GSAT evaluation, is provided in the Appendices.

2. DESIGN AND IMPLEMENTATION

2.1 Malaria in Indonesia

With a population of 242 millions and an area nearly three times that of Texas, Indonesia is the fourth most populous and the largest Muslim nation in the world. Situating next to the Strait of Malacca[†] that connects the Indian and the Pacific Oceans, it occupies a significant, strategic location. Indonesia consists of 30 provinces, 2 special regions (Aceh and Yogyakarta), and 1 capitol district (Jakarta Raya). The entire country has 440 districts (regencies), with the average district approximately twice as large as the average Texas county. An Indonesia map is included in Appendix B for reference.

Indonesia has yet recovered from the economic crisis that hit the Asian countries hard in 1997. It suffers from wide spread poverty, terrorism from extremists and separatists, troubled financial sectors, and a weak democracy. The tsunami tragedy at the end of 2004 puts further strains on the national economy.

In general, there is a scarcity of malaria epidemiological data. We have, however, managed to obtain the essential entomological and epidemiological datasets through the good will of the officials at World Health Organization (WHO) Southeast Asia Regional Office (SEARO) and colleagues at the Navy Medical Research Unit 2 (NAMRU-2).

In the following, we will describe the general malaria situation in Indonesia, the epidemiological data obtained from various sources, the ground based and satellite measured precipitation data we have acquired, an analysis on modeling malaria transmission with meteorological data.

Indonesia has the third highest malaria endemicity in Southeast Asia after Myanmar and India (WHO SEARO website, 2006). The distribution of malaria in Indonesia, however, is highly heterogeneous. On Java and Bali, malaria is hypoendemic. But on the Outer Islands, which include the rest of the archipelago, malaria ranges from hypo- to hyperendemic (Indonesian MOH, 2002).

The Malaria Subdirectorate in the Ministry of Health's (MOH) Center for Disease Control and Environment Health has the general responsibility for malaria control. Since 2001, as part of the overall decentralization efforts, the implementation of malaria control has been relegated to the district level.

The malaria control efforts include passive case detection, clinical diagnosis and treatment, and vector control. Only the districts on Java-Bali, where 70% of the total population concentrates, are equipped to provide also active case detection and laboratory diagnosis. Whether adequate resources and trained personnel are available and uniform practice is followed for malaria control across the districts are the obvious concerns. The Ministry of Health does not appear to have sufficient regulatory authority over the

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[†] Strait of Malacca is approximately 600 miles long. Its narrowest point is less than 2 miles wide.

districts. Due to resource shortage and perhaps weakness in the reporting structure, there is no centralized clearing house on malaria related data. Gathering reliable malaria epidemiological data is therefore a serious problem.

The Indonesia archipelago spans approximately 5,000 km. Within this wide geographic area, a number of anopheles species are the major malaria vectors, including *An. aconitus, An. balabacensis, An. farauti, An. koliensis, An. maculatus, An. minimus, An. punctulatus, An. sundiacus, An. Umbrosus.* The approximate distribution of these species are illustrated in Figure 1 (WHO & UNICEF, 2005). The main habitats, bloodmeal preference, and the biting and resting preferences are given in Table 1 (Lindsay *et al*., 2004; WRBU web site, 2007). How the larval habitats of these species are affected by and respond to climatic, environmental, and human-induced changes will be reflected in seasonal and longer-term variations in malaria transmissions. Understanding the ecology of these species also point to the way of using environmental management to reduce the propagation of malaria vectors.

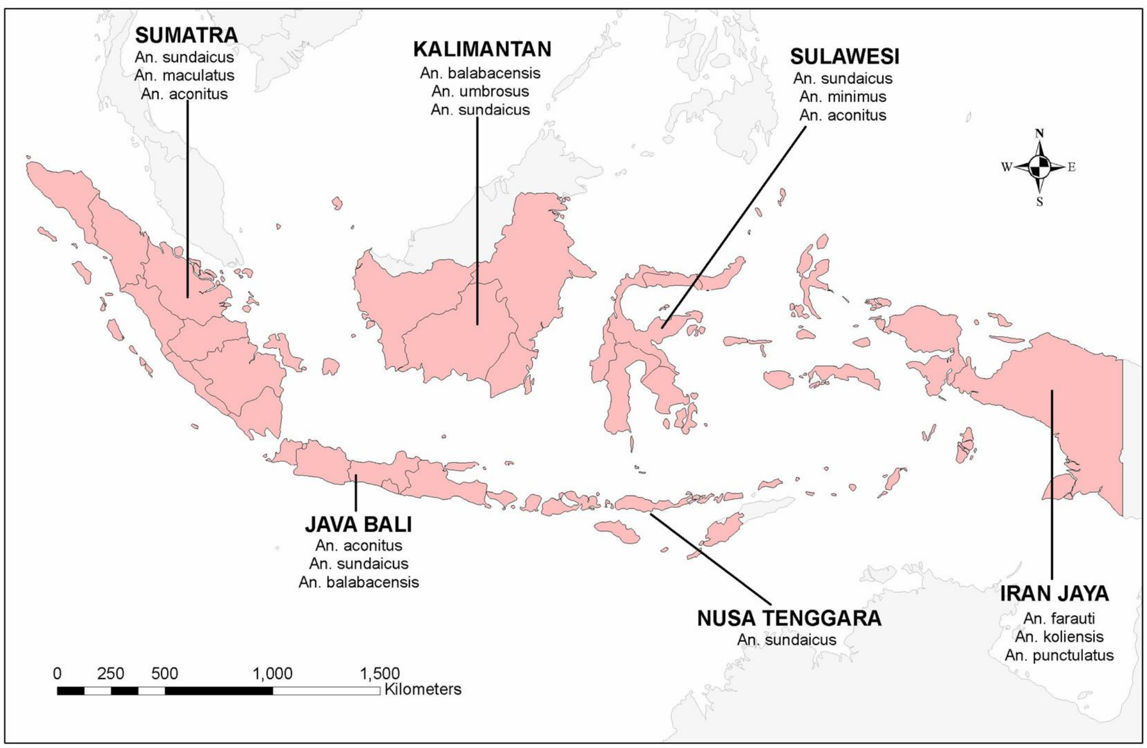


Figure 1. Distribution of major malaria vector species in Indonesia.

Table 1. Major malaria vector species in Indonesia, their habitats, and blood meals, biting, and resting preferences (based on Lindsay *et al.*, 2004; WRBU website, 2007).

Species	Islands	Habitats	Blood Meal	Feeding	Resting
A. aconitus	Java-Bali, Sumatra, Sulawesi	Prefer sunlit habitats: rice fields, swamps, irrigation ditches, pools, streams with vegetation	Humans and animals	Indoors and outdoors	Indoors and outdoors
A. balabacensis	Java-Bali, Kalimantan	Forest species similar to *A. diurs*. Muddy and shaded forest pools, animal hoofprints, vehicle tracks	Humans and cattles	outdoors	outdoors
A. farauti	Iran Jaya	Same complex as *A. punctulatus*. Sometimes breeds in wells, containers; brackish waters	Mostly humans	Indoors and outdoors	Indoors and outdoors
A. koliensis	Iran Jaya	Temporary pools in grassland areas in full sunlight	Mostly humans		Indoors and outdoors
A. maculatus	Sumatra	Prefer sunlight. In or near hilly areas, seepage waters, pools formed in streams, edges of ponds, ditches, rice field	Humans and animals	Indoors and outdoors	Mainly outdoors
A. minimus	Sulawesi	Prefer shaded areas of sunlit habitats. Flowing waters such as foothill streams, springs, irrigation ditches, seepages, rice fields, burrow pits	Mostly humans, domestic animals	Mainly indoors	Mainly indoors
A. punctulatus	Iran Jaya	Swamps, edges of flowing streams, springs, puddles, hoofprints, pools	Humans		
A. sundiacus	Java-Bali, Kalimantan, Nusa Tenggara, Sulawesi, Sumatra	Costal species but also found in fresh water inland pools. Prefer sunlight. Salt or brackish waters, lagoons, marches, pools, seepages	Humans and domestic animals	Indoors and outdoors	Mainly indoors
A. umbrosus	Kalimantan	Swamp-forest areas with dark acid waters under heavy shade	Humans	Indoors and outdoors	

2.2 Environmental Determinants for Malaria Transmission

The transmission of malaria is influenced by a myriad of factors. Environmental, climatic, social, and economic, public health, political, and warlike conditions have all been shown to contribute to malaria occurrence and outbreaks. Among these, the environmental conditions, especially rainfall, appears to be the most recognizable determinant. The intensity of malaria transmissions has long been associated with rainy seasons in human experience. The excessive rain or drought brought about by the climatic events like El Niño Southern Oscillation (ENSO) have also been shown to enhance the occurrence of malaria epidemics in the affected regions (Bouma & van der Kaay, 1996; Poveda *et al*., 2001; Githeko & Ndegwa, 2001; Gagnon *et al*., 2002; Kovats *et al*., 2003). Remote sensing is considered an important technology for predicting, preventing, and containing malaria epidemics (MARA/ARMA, 1998; WHO, 2001; WHO, 2004a; WHO, 2004b) because the environmental variables can be remotely sensed from satellites, and the likelihood of ENSO events may also be forecasted using satellite measured parameters. In recent years, researchers have used various methods and techniques that involves meteorological data or remotely sensed measurements for forecasting malaria epidemics, in particular for Africa (Thomson *et al.*, 1996; Hay *et al.*, 1998; Kleinschmidt *et al.*, 2000; Rogers *et al.*, 2002; Nalim *et al.*, 2002; Small *et al.*, 2003; Abeku *et al.*, 2004; Teklehaimanot *et al.*, 2004a; Teklehaimanot *et al.*, 2004b; Omumbo *et al.*, 2004; Thomson *et al.*, 2006). Some of the forecasting techniques may have already been used in operations (Grover-Kopec *et al.*, 2005). The advances in Geographic Information System (GIS) have also helped the integration of remote sensing measurements, epidemiological data, other information important to malaria transmission, and modeling results (Albert *et al.*, 2000).

Since rainfall provides vector breeding sites and prolongs vector life span by increasing humidity, precipitation or precipitation anomalies is the attribute most frequently used for predicting malaria epidemics. It has also been shown, however, that rainfall or the lack of it has a complex effect on malaria transmission for various parts of the world (Kovats *et al.*, 2003). For example, although moderate rainfall may promote malaria transmission, intense and prolonged rainfall may flush away larval habitats and thus reduce transmissions. Similarly, lack of rainfall does not always reduce larval populations. On the contrary, lack of rainfall may create new habitats, such as pools and puddles, in some regions and therefore increase larval population. In addition, droughts may be deleterious to predator populations or may cause human populations with no immunity to move to areas endemic with malaria (Kovats *et al.*, 2003). These factors may indirectly increase overall malaria transmissions. For regions where regular, yearly malaria infections contribute to partial immunity, a reduced transmission in certain years may increase the vulnerability in later years.

Another meteorological variable that is often used for predicting malaria transmission is temperature. Warmer temperature hastens larval and vector development and therefore increases the rate of vector production (Craig *et al.*, 1999). Higher temperature shortens the sporogonic cycle to allow vectors a longer period to transmit malaria. Warmer air also holds more moisture and therefore enhances mosquito survivorship.

Because malaria vectors have their preferred types of larval habitats (see for example, Table 1), the presence of certain vegetation types may indicate the presence of some malaria vector species. The notable example is rice fields, which are the larval habitats of *An. maculatus* and *An. sawadwongpor* in Thailand, *An. aconitus* and *An. minimus* in Indonesia, and *An. sinensis* in Korea. Another example is that the presence of *Ae. niveus*, the filariasis vector in Thailand, is associated with bamboos and bamboo cups, which are formed when the upper section of the bamboo is cut off. Identification of vegetation types needs satellite data with at least medium spatial resolution, and the expensive, high spatial resolution commercial data is sometimes needed.

2.3 Epidemiological Data

Considerable efforts were devoted to acquiring malaria data in Indonesia. The data we currently have at hand include:

A. WHO Southeast Asian Regional Office's database which includes both passive case detection (PCD) and active case detection (ACD). This dataset includes annual malaria cases from 1995 to 2003, and monthly cases from 1999 to 2003.

B. ASEAN Disease Surveillance Network's database which includes annual PCD malaria cases from 2001 to 2004.

C. Menoreh Hills Project dataset which is a joint effort between Indonesia Ministry of Health and WHO Roll Back Malaria. This dataset consists of two years of monthly data from 2000 to 2001. The latter part of the data may include both PCD and ACD data.

A and B are relatively large datasets compiled from data collected by the Ministry of Health and the Districts. Overall there are extensive data gaps in A and B, as well as inconsistencies within and between datasets. Comparing the data among administrative divisions and synthesizing a more complete picture on malaria transmission from these datasets is a challenging task.

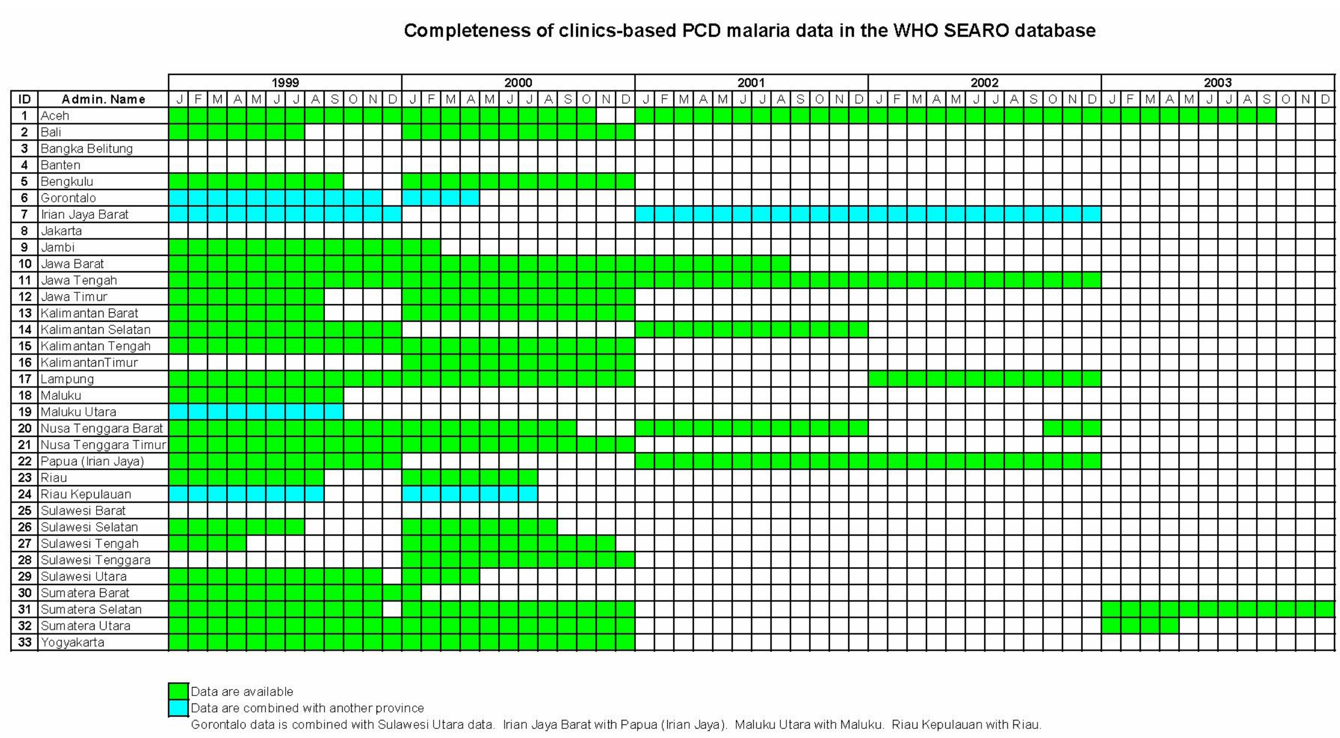
C is a small datasets. Because WHO's involvement in data collection, we believe its quality is higher. Dataset C, however, only concerns an area smaller than 3 districts in Central Java.

Of these three datasets, A and B are gridded data; and C is equivalent to point data because it covers three adjacent small regions.

2.3.1 <u>Data from WHO SEARO</u>

The database consists of monthly and annual data from ACD, MBS, and PCD. It primarily consists of provincial malaria cases, but has district level data as well for some provinces. This database does not differentiate malaria types – vivax, falciparum, mix or others. Table 2 shows the current extend of this database for the monthly provincial coverage.

Table 2. Completeness of the monthly malaria data in the WHO SEARO malaria database.



Slide Positive Rate (SPR) for Java-Bali in 2002 based on the WHO SEARO database is shown in Figure 2. For Java and Bali, blood samples were obtained from 0.7% of the total Java-Bali population in 2002. 5.4% of the samples were positive. The Slide Positive Rate (SPR) for Jakarta is not included in the figure because of insufficient information on samples taken there.

On the Outer Islands, health centers and treatment posts are responsible for malaria control. The annual malaria incidence per 1,000 population in provincial resolution is shown in Figure 3. The real situation may be much more serious that what was reported. WHO SEARO estimates that there are 15 million cases and 42,000 death annually in Indonesia, with the majority of morbidity and mortality from the Outer Islands (WHO SEARO website, 2006). The chloroquine resistant vivax malaria in Irian Jaya (Papua) and the chloroquine resistant malariae malaria discovered in Sumatra (Maguire et al.,

2002) are of great concerns. Because chloroquine and even Fansidar are freely available in Indonesia without prescription, self administered, incomplete treatment is most likely the cause for all three *Plasmodium* species to develop drug resistance.

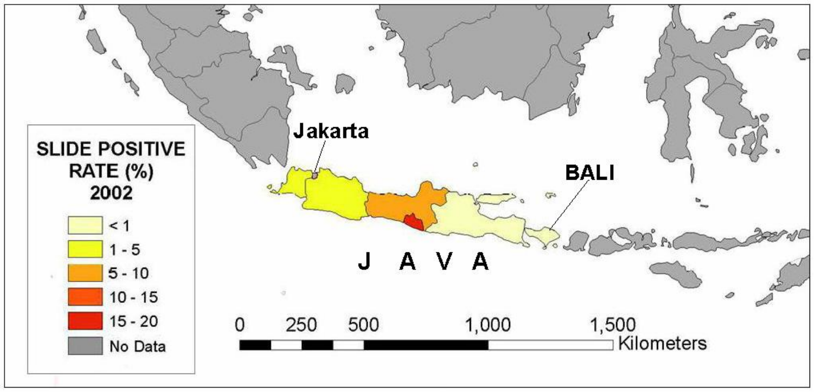


Figure 2. Slide Positive Rates for Java-Bali in 2002 based on the WHO SEARO database.

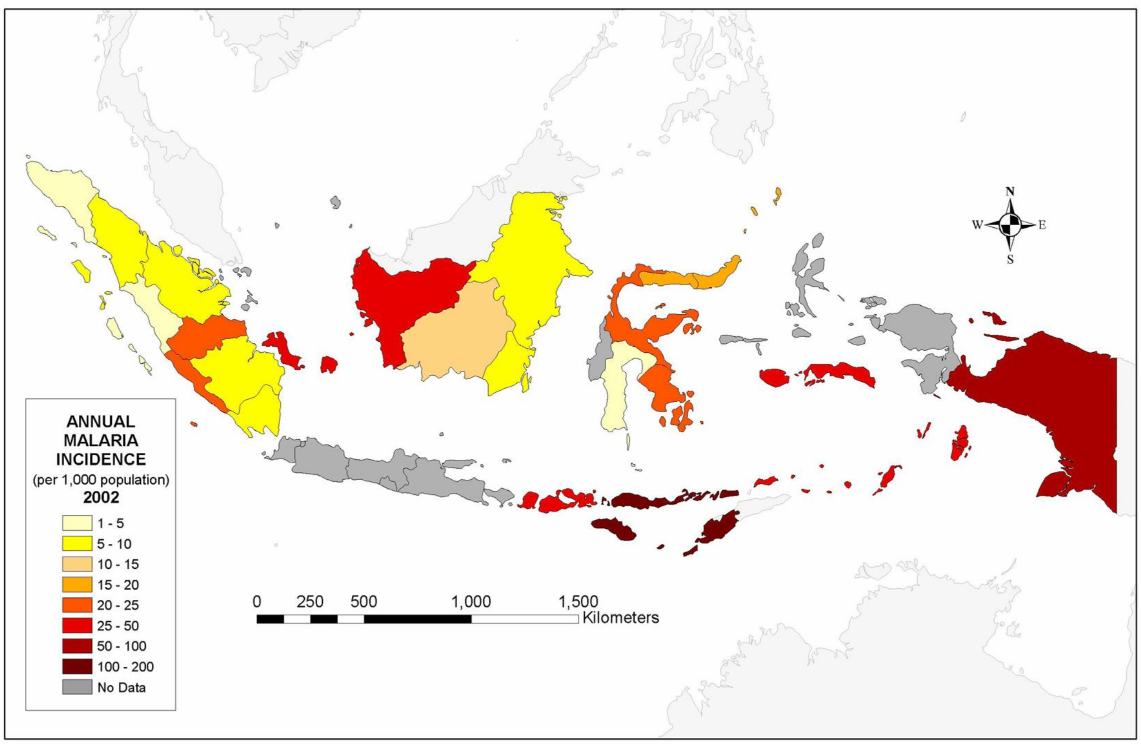
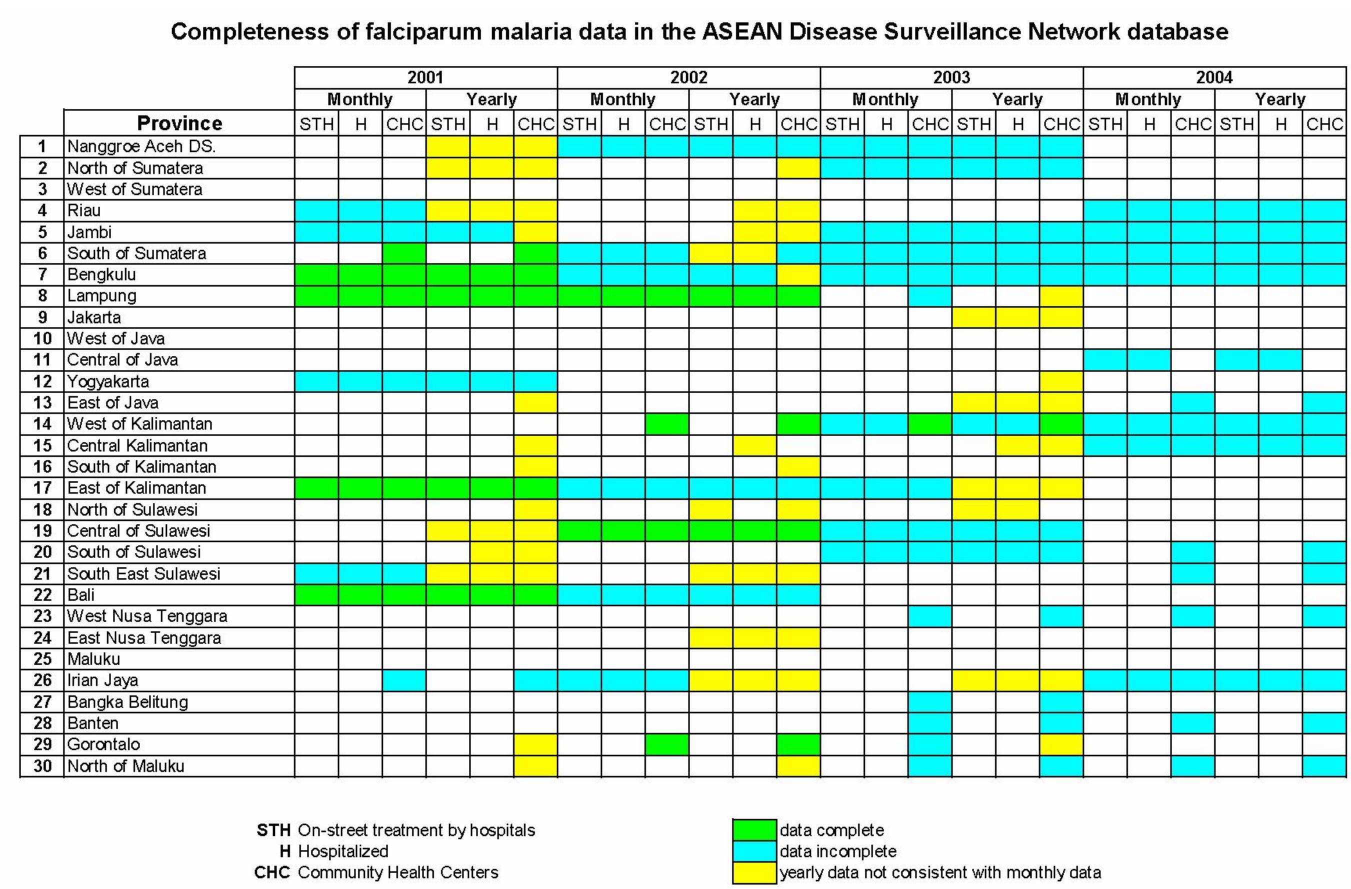


Figure 3. Annual Malaria Incidence per 1,000 population for the Outer Islands based on the passive case detection data obtained from WHO SEARO.

2.3.2 Data from ADSNet

We also obtained the ASEAN Disease Surveillance Network's (ADSNet web site, 2006) malaria database. This dataset is based on PCD. It differentiates the types of malaria and the types of facilities (hospitals, hospital's mobile units, or health centers) where the cases were detected. The malaria cases in this database are classified into 5 age groups (<1year, 1-4 years, 5-14 years, 15-44 years, and >45 years old). Some inconsistency between monthly and yearly malaria cases, however, need to be resolved. The vivax data is less complete than the falciparum data. Table 3 shows the completeness of the falciparum part of this dataset. Falciparum malaria case rates based on PCD for 2002 are shown in Figure 4. As explained earlier, the depicted case rates probably represent the lower bound of the true falciparum endemicity.

Table 3. Completeness of the falciparum malaria data in the ASEAN Disease Surveillance Network database



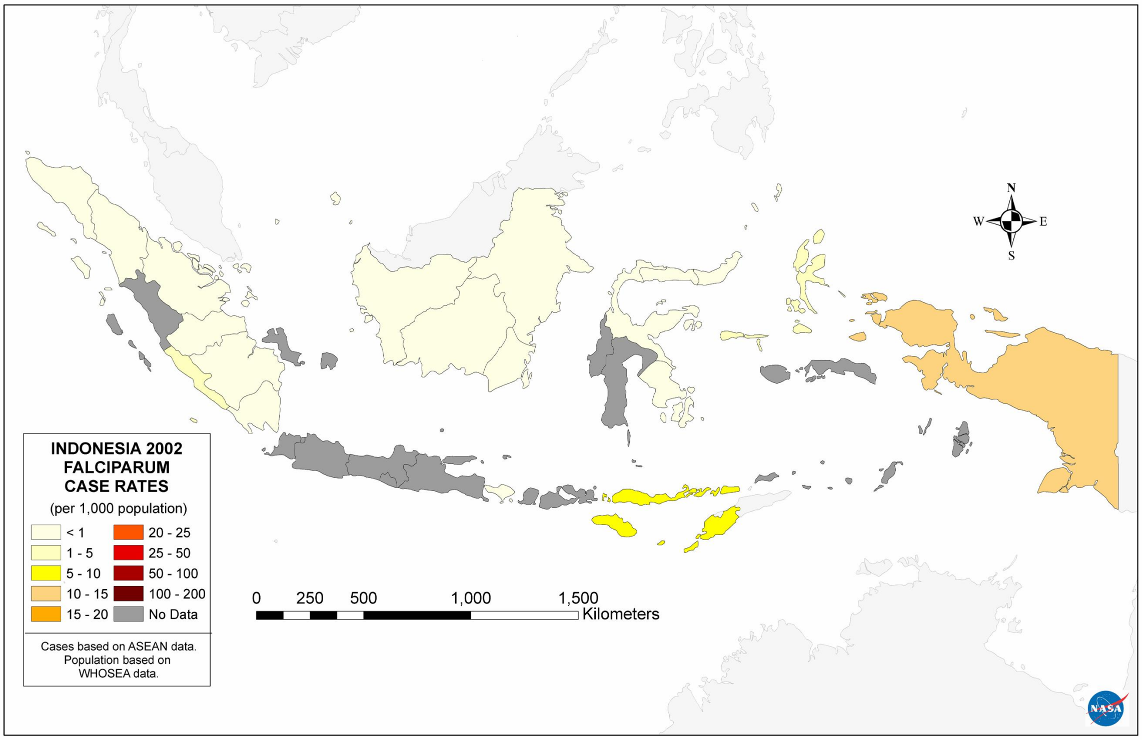


Figure 4. Provincial falciparum malaria case rates (per 1,000 population) in 2002 based on ASEAN Disease Surveillance Network data.

2.3.3 Data from MOH-WHO RBM

We have also obtained the data from the 7-month Menoreh Hills malaria project (2001-2002) as well as a 24-month malaria time series (2000-2001) used by the project (Indonesian MOH report; Indonesian MOH, 2002). Menoreh Hills is an area in Central Java (Jawa Tengah) with persistent malaria transmission. Geographically, it spans parts of three districts – Purworejo, Kulon Progo, and Magelang. This project was a MOH-WHO RBM collaboration with funding provided by USAID. PCD, MBS, and Mass Fever Survey (MFS) were used in the project. Because the latter part of the malaria time series may include both PCD and MBS/MFS data, it is difficult to express the time series in case rates. Based on the MBS and MFS results quoted in the report, the approximate endemicity for vivax and falciparum together is 20% for Purworejo, 10% for Kulon Progo, and 10% for Magelang. Because of WHO's involvement, these survey results should be relatively reliable.

An. maculatus and *An. balabacensis* are the main malaria vectors in this region. Both species prefer animal bloodmeals, and feeding and resting outdoors. Despite these zoophilic and exophilic preferences, they are responsible for the malaria transmissions in this region as well as in Thailand (*An. balabacensis* is similar to the *An. dirus* in Thailand.)

In the Menoreh Hills region, normally there are two annual transmission peaks – one during the dry season (June-August), and another during the rainy season (November-January). There are hypotheses that different malaria vectors are responsible for the two transmission peaks. The 24-month time series of malaria cases through MBS are shown in Fig. 10. The two transmission peaks may merge if there are meteorological abnormalities.

2.4 Meteorological and Environmental Data

Since the malaria data we have obtained consist of both point and area-wide measurements, we have been acquiring both ground-based and satellite-measured meteorological data.

Germany's Global Precipitation Climatology Center (GPCC web site, 2007) is a World Meteorology Organization (WMO) sponsored institution. It compiles and analyzes precipitation data for climate research. GPCC's dataset is based on measurements at more than 40,000 ground stations provided by approximately 170 countries. The gridded data is in 0.5°×0.5° resolution. Data with higher resolution will be available in the future. The GPCC data for May 2002 is shown in Figure 5 as an example.

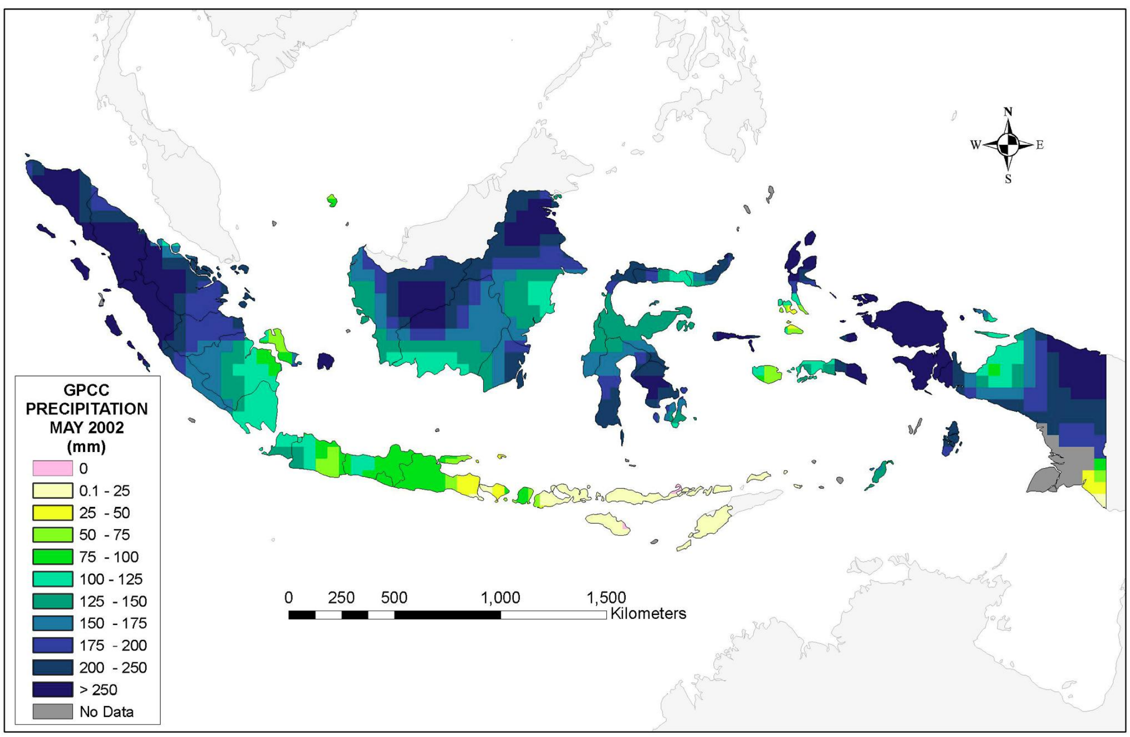


Figure 5. Rainfall distribution in May 2002 based on GPCC data.

As in the malaria study for Thailand, we use NASA's Tropical Rainfall Measuring Mission (TRMM) data to provide rainfall information in this study as well. TRMM (Kummerow *et al.*, 1998) is a joint mission between NASA and the National Space Development Agency (NASDA) of Japan. It was launched in November 1997. The mission is expected to end in 2009. Its successor will be the Global Precipitation Measurement (GPM) mission, which is an international collaboration and involves a constellation of satellites (Smith *et al.*, 2006). The TRMM dataset provides a precipitation estimate from multiple global data sources, including TRMM, infrared measurements from geo-synchronous satellites, and rain gauges. These gridded estimates are at 0.25°×0.25° resolution and monthly interval, with a coverage between 50°N and 50°S. Provincial rainfall in May 2002 derived from TRMM data is shown in Figure 6 as an example.

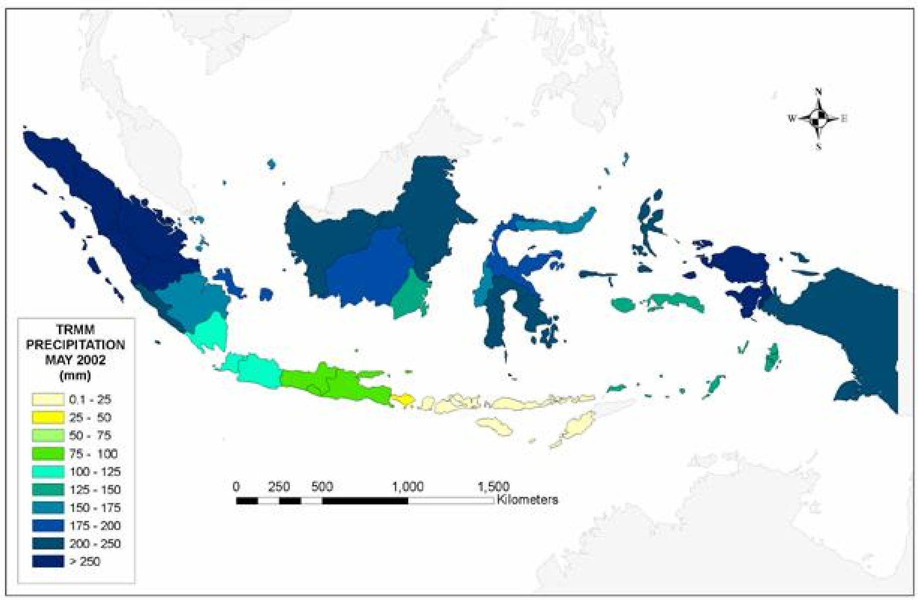


Figure 6. Provincial rainfall distribution in May 2002 based on TRMM data.

The rainfall patterns on the eight major islands vary significantly. To illustrate the variation, the average monthly precipitation for the major cities on the eight islands from 2000 to 2005 are shown in Fig. 7. On Java and Bali, the two main islands, the wet season lasts approximately from October to April. And the dry season is from May to September. On other islands, however, the rainfall pattern can be very different. For example, the wet and dry seasons are less pronounced on Kalimantan and Irian Jaya. The dry and wet seasons on Maluku are opposite to those on Java and Bali. On Sumatra, at Medan at least, there is a different rainfall pattern. In Nusa Tenggara, which include Timor, there can be drought in the dry season. Because precipitation is the most important environmental determinant in driving malaria transmission, different rainfall patterns will lead to different malaria transmission pattern. This is evident when comparing the malaria transmission in Jawa Tengah (Fig. 8) on Java and Nanggore Aceh Darussalam (Fig. 9) on Sumatra.

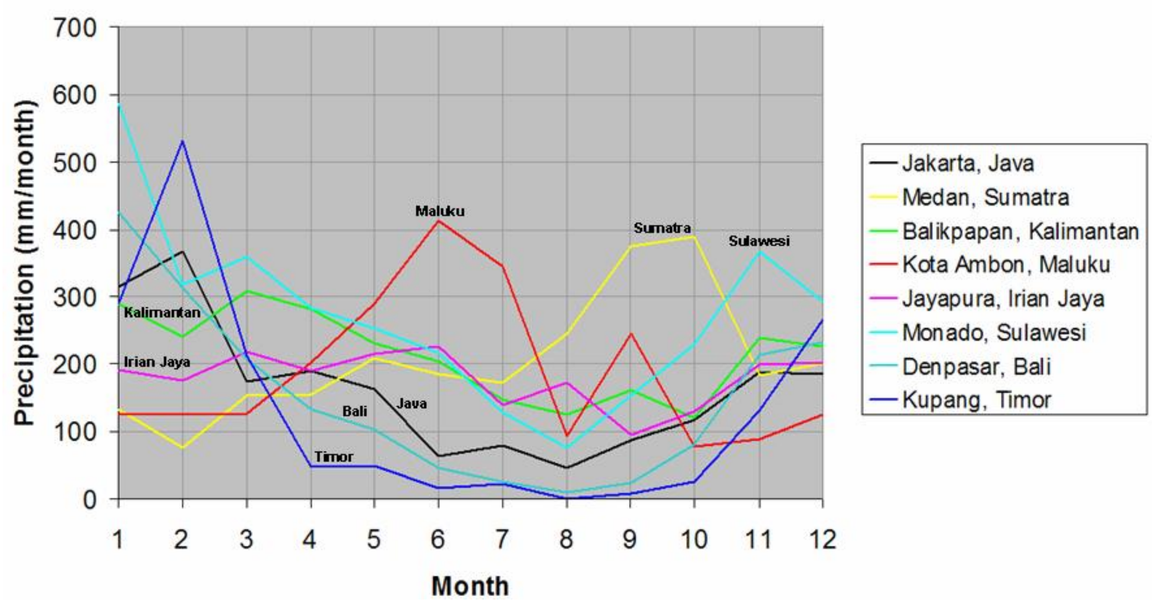


Figure 7. Average monthly precipitation from 2000 to 2005 for the major cities on the eight islands.

2.5 Modeling Malaria Risks

We use the neural network (NN) method to approximate the dependency of malaria cases on the meteorological and environmental variables. This method has been successfully used in many applications, including classification, regression, time series analysis, and handwritten character recognition (Nelson & Illingworth, 1990). In this approach, the probability density of the data is not assumed to follow any particular functional form. Rather, the characteristics of the probability density are determined entirely by the distribution in the data, hence, it is a data driven approach. This method is most suitable for problems that are too complex to be expressed in a closed, analytical form. For problems in which there are hidden, implicit variables, this approach is particularly suitable, as it is difficult to either specify the variables properly or sufficiently account for their effects mathematically.

To train our neural network model, we feed observed or measured parameters from the past into the network. The input parameters may consist of meteorological, environmental, and other variables and the output parameter is the corresponding malaria cases for that specific location and time. Once trained, the network will be able to estimate the cases at some other time period using the parameters corresponding to that time period.

The neural network used in this analysis is in the class of multi-layer perceptron (Rumelhart & McClelland, 1986; Haykin, 1994; Bishop, 1996). The general network architecture is composed of an input layer, one or more hidden layers, and an output layer. Each layer consists of a number of nodes. In this analysis, meteorological and environmental data are the main parameters fed into the input layer; and the malaria cases or other data indicating malaria prevalence are the parameters generated from the output layers. A hidden layer consists of one or more hidden nodes. The function of the hidden layers in a neural network is to map the data structure into a new representation that facilitates the optimization of the objective function. For example, if the objective function is to maximize classification accuracy, hidden layers will transform the input parameters into functions of the parameters to make the classes more readily separable. Without hidden layers, a neural network may only differentiate linearly separable classes. Because the complexity of the data structure and the objective function drive the construction of hidden layers, trial and error is the usual approach to determine the numbers of hidden layers and hidden nodes to be used. In fully interconnected networks, weight decay (Bishop, 1996) can be used to eliminate nodes and links that are insensitive to the optimization of the objective function.

In the hindcasting (or retrospective forecasting) mode, the model is used to estimate the historical cases. The model's estimation accuracy can then be determined by comparing the model output with the events that took place in the past. Moreover, future malaria cases can be predicted by using forecast parameters as input in the forecasting mode. Once a model is trained with past epidemiological data for a region, estimates on current malaria endemicity for that region can also be obtained by feeding current meteorological and environmental data into the trained model.

We developed the majority of the processing, modeling, and analysis software in IDL, Matlab and C, including a neural network code in C. Commercial software used in this study includes ENVI/IDL, Matlab, NeuroSolution, and ArcView.

3. V&V METHODS AND RESULTS

Comparing with the malaria time series for Thailand provinces, the time series for Indonesia are generally much shorter and incomplete (see Tables 2 and 3). Because fewer data points are available for modeling, the number of variables (or covariates, or degrees of freedom) must be reduced to preserve the ability for generalization.

Indonesia is situated from 5ºN to 10ºS across the Equator. Humidity is high year round in this environment, and hence not an important factor in determining the variation of malaria transmission. Although malaria vectors' larval habitats are associated with certain surface types or vegetation, high spatial resolution data is normally needed to identify the surface and vegetation types. Vegetation indices derived from data with low to medium spatial resolution can be used for inferring recent precipitation in arid or semi-arid regions where precipitation data is not available. Such inference is less feasible for regions where ample precipitation is normally received, and unnecessary if precipitation data can be obtained through other means. Consequently, both relative humidity and vegetation index will not be included as independent variables in modeling to reduce the degrees of freedom.

We use two provinces – Jawa Tengah and Nanggroe Aceh Darussalam (NAD) as examples to illustrate training and prediction using neural network methods. Jawa Tengah means Central Java, and NAD is the province that suffered tremendous, tragic loss in the December 2004 tsunami. The independent variables for training include current and last month's precipitation, temperature, time and last month's endemicity. The time factor is included to accommodate for trend that is not related to meteorological variables but more likely due to socioeconomic and anthropogenic factors. These factors may include road building, deforestation, military conflict, economic crisis, and public health support.

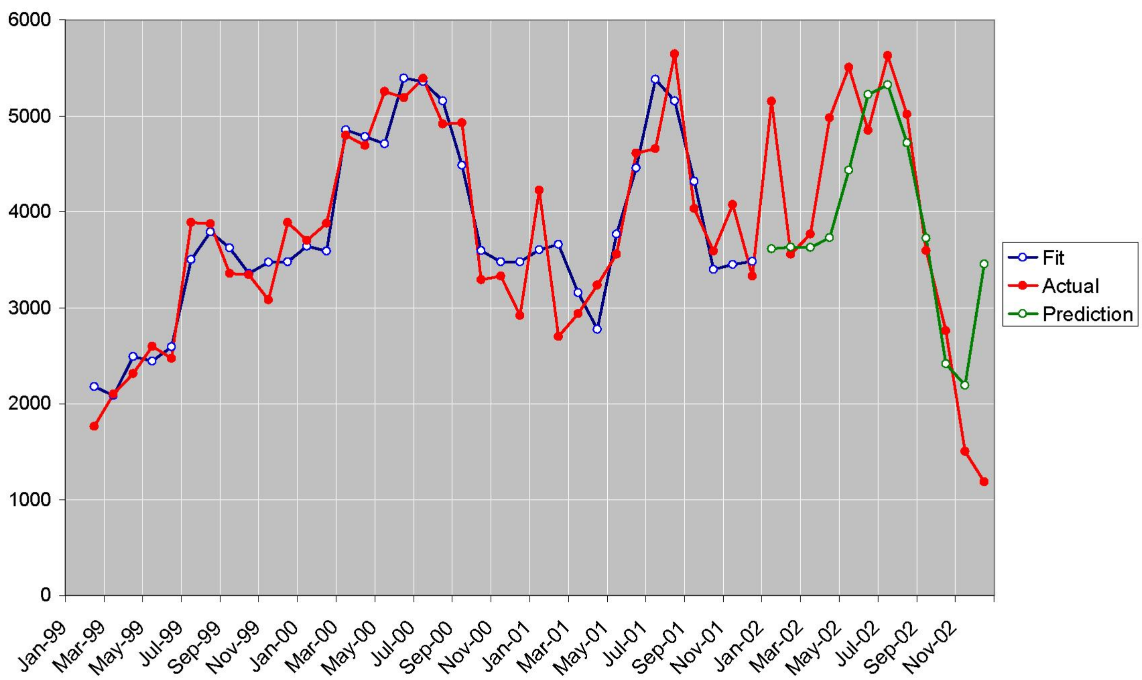


Figure 8. Malaria cases time series (red) for Jawa Tengah Province. Modeled cases are in blue, and hindcast cases are in green.

In Fig. 8, the malaria time series of the Jawa Tengah Province and input parameter between February 1999 and January 2002 are used for training. The actual parameters from February 2002 to December 2002 are then input in to the trained network to hindcast the malaria cases. It is observed that the hindcast cases closely approximate the observed malaria time series. The difference between the observed and hindcast time series is due to factors that are unrelated to meteorological and climatic condition, such as the socioeconomic and anthropogenic factors described previously.

Similary, Figure 9 shows the training and hindcast results for the NAD Province. The hindcast result approximates the actual time series well.

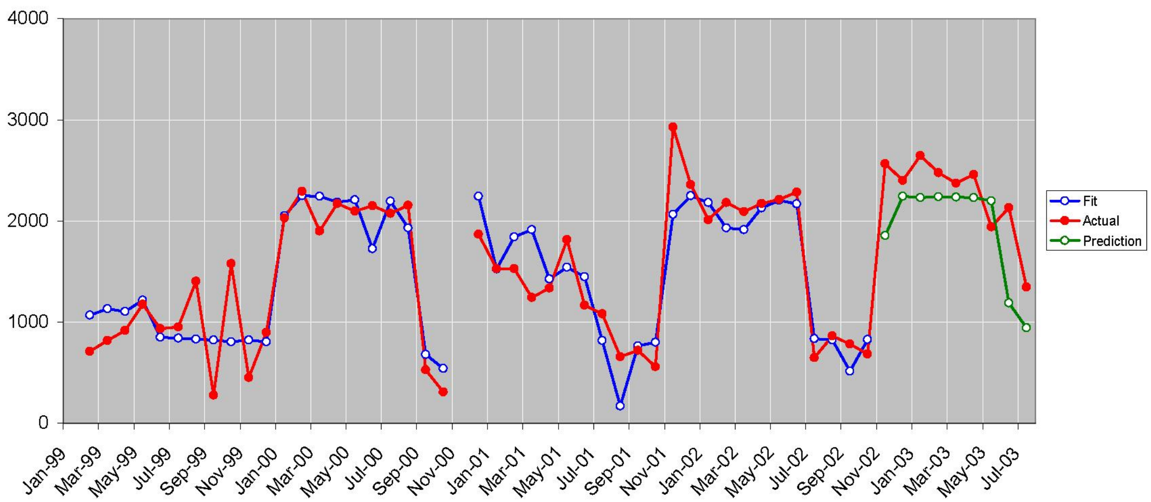


Figure 9. Malaria cases time series (red) for NAD Province. Modeled cases are in blue, and hindcast cases are in green.

As described in Section 2.3, Menoreh Hills is a region in Central Java with persistent malaria transmission, despite that the rest of Java has very low endemicity. Since the Asian economic crisis in 1997, the malaria vector control efforts were interrupted and the situation worsened.

It is difficult to implement larval control because of the topography of this region. There are hundreds of small streams on the hill which are not easily accessible. These streams swell with the rainfall. But after the water recedes, the drying stream beds create infinite number of small pools which become the breeding sites of *An. maculatus*. Construction of dams and timely flushing may reduce such breeding sites if resources are available. But in general, any larval control method is difficult to implement because of the terrain in this region.

Fig. 10 shows the active case detection (ACD) malaria time series as well as fitted and hindcast results for Kulong Progo and Purworejo, two districts in the Menoreh Hills region. The training results agree with the malaria time series well. Because the ACD time series are only 2-year long, no data can be spared from training to test against hindcast result. Because Menoreh Hills is part of the Jawa Tengah Province, we compare the Jawa Tengah PCD time series with the sum of actual and hindcast time series of Kulong Progo and Purworejo ACD data in Fig. 11. These time series were collected by different teams with different methods for different objectives. Because people infected with malaria may be asymptomatic or only have minor clinical symptoms, ACD cases should be more than PCD cases. Although Menoreh Hills is part of Jawa Tengah, the endemicity of Jawa Tengah is low. Therefore comparison of these two time series is still qualitatively meaningful.

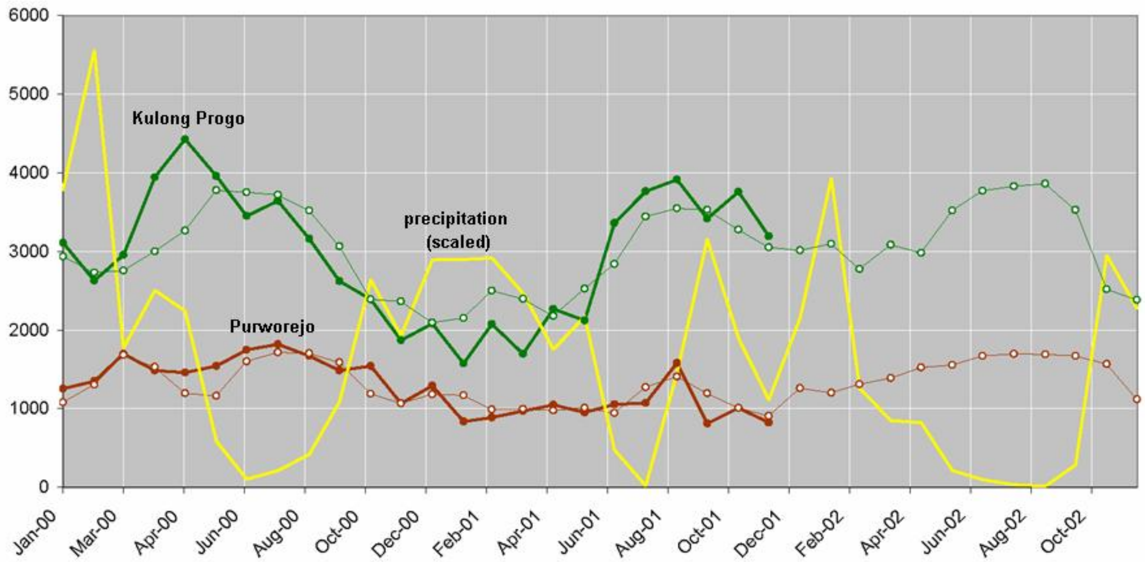


Figure 10. Malaria cases time series (heavy) for Kulong Progo and Purworejo Districts. Fitted and hindcast cases (thin) are also shown.

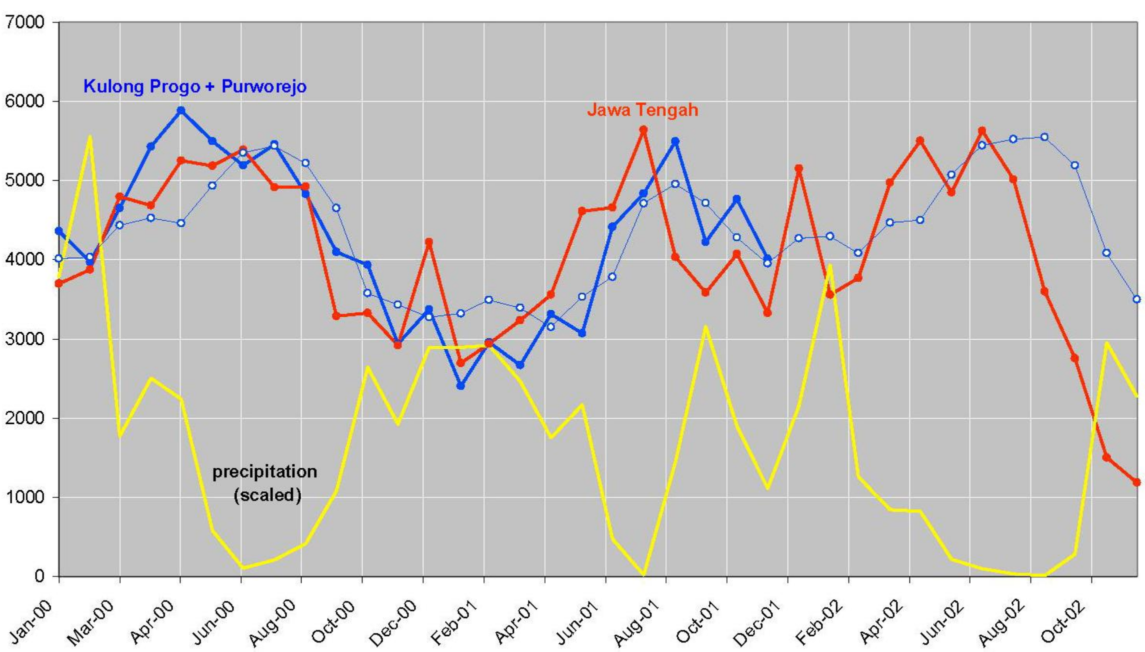


Figure 11. Comparison of Jawa Tengah PCD time series (heavy red) with the sum of Kulong Progo and Purworejo ACD time series (heavy blue). The fitted and hincast time series (thin blue) are also shown.

After July 2002, there appeared a significant drop in PCD cases in comparison with the hindcast ACD cases, which was obtained according to reasoning of the variation of environmental parameters. This may indicate that the continuous ACD in Menoreh Hills results in lower endemicity at the end of this two-year project, beause in such studies all positive residents are given treatment regardless of the presence or absence of symptoms.

We have observed similar phenomenum at Bang Kong Mong Tha, the Thailand test site (Zollner et al.). ACD is undoubtedly the most effective, but also the most costly, method to reduce endemicity.

4. DATA LIMITATION IN V&V

We have shown, through training and hindcasting, that the neural network model can reasonably well model the dependency on meteorological and environmental parameters and predict future cases. The development and V&V of the model, however, are limited by the availability of malaria data.

Because there is no centralized malaria database, completeness and reliability of the datasets depends on the effort and the judgment of the compiling organization, as well as the cooperation of the public health organizations that hold the data. In a decentralized environment with weak regulatory policy and reporting structure, it is difficult to know whether data were collected with consistency or not among the multiple levels of health services (hospitals, clinics, health centers, mobile units, and volunteer treatment posts, etc.) It is therefore difficult to decide whether to include or reject data with ambiguous quality and history when compiling the datasets.

Our collaborators at NAMRU2 do occasionally conduct active case detections or mass blood surveys when requested by the public health agencies in the host countries. These data, while undoubtedly have better quality than the average epidemiological data available in these countries, the sample size is usually small due to the limited scope of the surveys. The geographical distribution of the sampling points is also often limited. In addition, active case detection or mass blood survey are usually conducted at locations with ongoing or recent outbreaks. The slide positive rates at these locations are therefore higher than the endemicity in the general populations. Consequently the data may not be sufficiently representative for verifying the performance of the MMS risk assessment model.

5. CONCLUSIONS

Previously we have used Thailand malaria data to show that our neural network based techniques along with NASA data can estimate current and future malaria endemicity with reasonably good accuracy. We have also concluded that such results and capability are needed by our decision support partner to assess malaria risks for U.S. overseas forces.

A previous concern was whether this methodology and NASA data could equally well be used for malaria in other parts of the world. This concern is legitimate because malaria vector species, their larval habitats, parasite species, environmental determinants, and socioeconomic factors that promote or prohibit transmission indeed have large variation from region to region. Although the mathematical formulation for risk prediction may remain the same in the broad sense, conceivably there may be variation needed to adjust for the specificity for the malaria transmission in a region. We therefore welcome the opportunity to put our techniques to test using Indonesian data.

The challenge of assessing malaria risks in Indonesia is how to model the risk when malaria time series are short and incomplete. And because of the decentralized public health service and disease monitoring and control efforts, there is concern that whether human malaria data were consistently collected.

In general, malaria transmission depends on the diverse factors that influence the vectors, parasites, human hosts, and the interactions among them. These factors may include, among others, meteorological and environmental condition, the innate and adapted immunity of the human hosts, public health system, housing standards, vector control, road construction, irrigation projects, and population movements. The couplings among these factors may be so complex that it is difficult to isolate the key factors that promote or sustain malaria transmission in an area.

The most apparent determinants are the meteorological and environmental factors, such as rainfall, temperature, humidity, and vegetation. For example, human experience has shown that malaria is correlated with the rainy season, and that ENSO events may either increase or decrease malaria transmission. When other factors remain more or less constant, the meteorological and environmental conditions can indeed be considered the driving factors. These conditions can be remotely sensed using satellites that regularly cover extensive geographical areas.

Because of the scarcity of malaria data in Indonesia, we have decided to use fewer independent variables in order to reduce the degrees of freedom and improve generalization. The two geophysical parameters excluded from modeling are relatively humidity and vegetation index. Both parameters are deemed less significant in comparison with other variables.

Using Indonesian malaria data, we have shown that neural network techniques are a useful approach for modeling the dependency of malaria cases on meteorological and environmental parameters. Neural network is a vital part of machine or artificial intelligence, which is a discipline to study machine's ability for learning and adaptation, and exhibition of intelligent behaviors. In general, the neural network techniques are superior to generalized linear models, because linearization are subjective and may not be optimum.

The risk assessments from the MMS project will allow the U.S. overseas forces to be better prepared for malaria prevention and in responding to malaria morbidity. In the Armed Forces, there are other Decision Support Systems similar to GSAT that provide risk assessments on infectious diseases. These systems exchange information with one another. The beneficial returns of NASA data and results will be multiplied as the results from the MMS project are shared with other Decision Support Systems.

During peacetime or wartime, U.S. overseas forces work with the local public health organizations to reduce disease risks among the general populations. The outcome of the NASA MMS Project will therefore help reduce the morbidity and mortality among the local populations. The risk assessments will also facilitate more targeted insecticide and larvicide applications, and therefore reduce the potential damages to the environment and the risk of insecticide resistance.

Appendix A. Summary of MMS-GSAT Evaluation from V&V Report Part 1

The goals of AFSOC's GSAT and NASA's MMS Projects are clearly compatible. In the Evaluation Report, we concluded that the NASA data, results, and the output from MMS will be able to enhance GSAT's capability.

The NASA data and results to be provided to GSAT include: 1) the satellite derived meteorological and environmental parameters; 2) malaria risk maps for selected regions of the world that are jointly agreed upon by AFSOC and NASA teams; and 3) potential malaria vectors' larval habitats for selected areas. The NASA team will further develop its malaria modeling capabilities to assess malaria risks for regions of interest to AFSOC, while the AFSOC team will integrate malaria risks and NASA Earth-Sun science data into GSAT. The GSAT will also be tested by AFSOC 18th Flight Test Squadron and in real military exercises.

When GSAT is fielded, the Air Force will gain a computerized environmental and medical planning capability. The combined capabilities of the malaria assessments and GSAT will provide the U.S. Air Force, Department of Defense, and its partners with a decision support tool valuable to U.S. military and civilian sectors. Because U.S. overseas forces generally assist the local public health organizations in disease prevention and control, the enhanced GSAT will also benefit the local populations.

Appendix B. Map of Indonesia

Map No. 4110 Rev. 4 UNITED NATIONS

Department of Peacekeeping Operations

ACRONYMS

AFRIMS	Armed Forces Research Institute for Medical Sciences
AFSOC	Air Force Special Operations Command
AVHRR	Advanced Very High Resolution Radiometer
CCD	Cold Cloud Duration
DAAC	Distributed Active Archive Center
DST	Decision Support Tool
ENSO	El Niño Southern Oscillation
EOS	Earth Observing System
GIS	Geographic Information System
GMS	Greater Mekong Subregion
GPM	Global Precipitation Measurement
GSAT	Global Situational Awareness Tool
MMS	Malaria Modeling and Surveillance
MODIS	Moderate Resolution Imaging Spectroradiometer
MOPH	Ministry of Public Health (Thailand)
NAMRU-2	Naval Medical Research Unit-2
NCAR	National Center for Atmospheric Research
NCEP	National Centers for Environmental Prediction
NDVI	Normalized Difference Vegetation Index
SIESIP	Seasonal-to-Interannual Earth Science Information Partner
TRMM	Tropical Rainfall Measuring Mission
V&V	Verification and Validation
WHO	World Health Organization

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